

# Real-Time Mental Stress Monitoring Using Machine Learning on User Interaction Patterns

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## Abstract

The detection of mental stress is becoming an essential function of modern Human Computer Interaction (HCI) systems due to its effects on user performance and mental well-being. This work introduces a novel real-time system to monitor mental stress by using machine learning techniques on non-invasive behavioural biometrics. The system collects data from user interaction through keyboard dynamics (typing speed and latency), mouse behaviour (jitter and click frequency) and eye-tracking (using Eye Aspect Ratio, EAR, derived by using Media Pipe). We employ a Long Short-Term Memory (LSTM) model in order to capture the temporal patterns within the user's behaviour and the Isolation Forest algorithm for anomaly detection by identifying the discrepancies with the user's individual baseline pattern. A user-specific modelling approach with user-specific normalization is integrated into the system to adapt the model to the specific characteristics of each user. The proposed system employs an efficient SQLite lightweight database to store sessions and update the model accordingly. Our results show better performance based on F1-score and more resilience towards biased behavioural data than other approaches while keeping the low latency characteristics of the proposed system which make it a good candidate for real-time monitoring applications.

**Keywords:** Stress Monitoring, Behavioural Biometrics, Long Short-Term Memory (LSTM), Isolation Forest, Human-Computer Interaction, Real-Time Intervention.

## 1. Introduction

Mental stress within the computer environment has been witnessed in the age of computers for many users and this effects user performance, efficiency and their overall health. While computers become an integral part of human life and use increases; the call is arising for an intelligent system that is aware and responsive to the user stress in real time. In the past, human stress has been detected through the use of physiological signals such as Heart Rate Variability (HRV), Electroencephalogram (EEG), and Skin Conductance (SC). These prediction methods yield accurate results but it is impossible to apply due to its dependence on specific sensors, invasiveness and unsuitable for real time applications with long term deployment. The

advancements in the Human-Computer Interaction (HCI) domain has opened new pathways for unobtrusive real time human stress detection through behavioral biometrics.

The user interaction signals such as the typing dynamics, mouse movements and gaze directions contain useful and crucial information concerning both the cognitive load and emotion without adding a new piece of hardware to the system. As this signal is being continuously generated and used during computer operation it is well suited to be the primary input to a long term and unobtrusive human stress detection system. However behavioral signals are intrinsically complex and noisy, and can vary greatly between users, which can affect standard machine learning algorithms' performance.

Hence, in this research a real time human mental stress detection system is presented using a multi modal system with inputs taken from keyboard dynamics, mouse behavior, eye-tracking features through Media Pipe. This input is then given through hybrid architecture of Long Short-Term Memory (LSTM) network and Isolation Forest to effectively deal with the temporal sequence and anomalies as well as providing individual tailored output with respect to a baseline of the user. The output does not just indicate stress, but rather real time intervention is provided to the user in the form of alert messages on the screen which can aid the user to adjust to their stress levels by having small break or rest. To keep the system efficient a learning method is implemented and a light database (SQLite) is maintained for storing user sessions.

## 2. Related Work

The assessment of the psychological state of users through computer interaction has been an important research topic over the past few years. One of the earliest findings states that keystroke and mouse dynamics are reliable indicators of the user's mood and workload [1]. Recent literature surveys on mouse behavioral biometrics have outlined the opportunities in non-intrusive behavioral signals for continuous and passive monitoring [8].

An important survey conducted by Yang and Qin (2021) on emotion recognition through interaction was very descriptive regarding this topic. They explained that keyboard and mouse dynamics have been used successfully, but the features are user-dependent [7]. Their work from 2025 continues the work about user-dependent variables and the keystroke and touchscreen dynamics [3].

In controlled and simulated settings, a combination of multimodal approaches yields high accuracy rates. A study conducted by the usage of eye-tracking activity and RNN to detect the response to a physiological stressor was successful and reached accuracy levels of over 95% [2]. A hybrid use of multiple behavior streams (i.e., mouse movement, keyboard input) was employed in office environment to detect stress patterns and interpretable machine learning techniques were applied [4].

Regarding user specific investigation: the use of mouse jitter and speed was proposed as potential behavioral stress indicators [6], even though these indicators could be challenging in terms of cross hardware performance. Consumer electronic applications using those behavioral dynamics were successful in determining the base line for monitoring [9]. However, most of the implemented systems use purely temporal models or static anomaly detection. The current work provides an LSTM and Isolation Forest hybrid architecture in order to take into account both temporal dynamics and user specific behavior patterns at once.

## 3. Methodology

This framework is a proposed as an asynchronous and modular real-time pipeline to recognize mental stress from non-intrusive behavioral patterns. The framework follows a layered structure which encompa-

esses data acquisition, feature engineering, and system integration.

### 3.1 Multi-Modal Data Acquisition Layer

The goal of this layer is to unobtrusively collect user's behavioral data in real time from natural computer usage.

Data are collected via 3 main channels:

**Keyboard Dynamics:** Behavioral features from typing behavior are captured such as wpm, number of keys pressed and number of typing errors. Analysis of keys pressing delay, duration of hold (dwell time) and between press time (flight time) will allow us to detect mental stress in the user's typing behavior.

**Mouse Interaction:** Cursor trajectory is collected and used to analyze the speed, rate of click, and jitter of cursor. Parameters such as time of click delay, time that the user didn't use mouse (idle time), and rate of cursor acceleration will be calculated to determine if the user movement is shaky due to their mental state.

**Computer Vision and Eye-Tracking:** Facial features will be captured using web cam with the help of MediaPipe library that extracts the facial landmark on high resolution. Vision-based metrics like blink rate, gaze stability (variance of eye positions) and Eye Aspect Ratio (EAR) will be collected from video feed and to determine user's exhaustion and stress level using ordinary webcam.

### 3.2 Feature Engineering and Time-Windowing

Collected raw log from sensing layer will be processed into a standardized set of features with the help of window segmentation module.

**Window Segmentation:** The raw data will be split into short time windows. In the designed framework, time window is 3 seconds for active tracking and 2 seconds for calibration.

**Statistical Operations:** Features will be derived using statistics like mean, standard deviation, variance on each collected raw data in a window. The mean and variance of user's eye movement consistency or speed of mouse movement, for example, are collected.

**Normalization:** Before feeding to the model, all the features will be normalized using per-user and per-session data so that the model will be invariant from different hardware qualities or user typing speed.

### 3.3 System Architecture and Storage Integration

Architecture is designed in the form of layered structure to realize low-latency detection and management of collected data.

**Hybrid Machine Learning Engine:** A hybrid model architecture of LSTMs and Isolation Forest is designed which analyze the time-sequence features from the feature extraction layer and anomalies detection respectively.

**Data Storage:** Light-weighted SQLite database will be integrated to manage per-user profiles, sessions and individual behavioral baseline data.

**Eye Aspect Ratio (EAR) Formula:** EAR that is used for blink detection and analyze user's exhaustion/stress are calculated as:

$$EAR = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2 \cdot ||p_1 - p_4||} \quad (1)$$

**Visual Representation:** The overall flow, from capturing raw logs to providing real-time intervention alerts, is illustrated in the architectural framework.

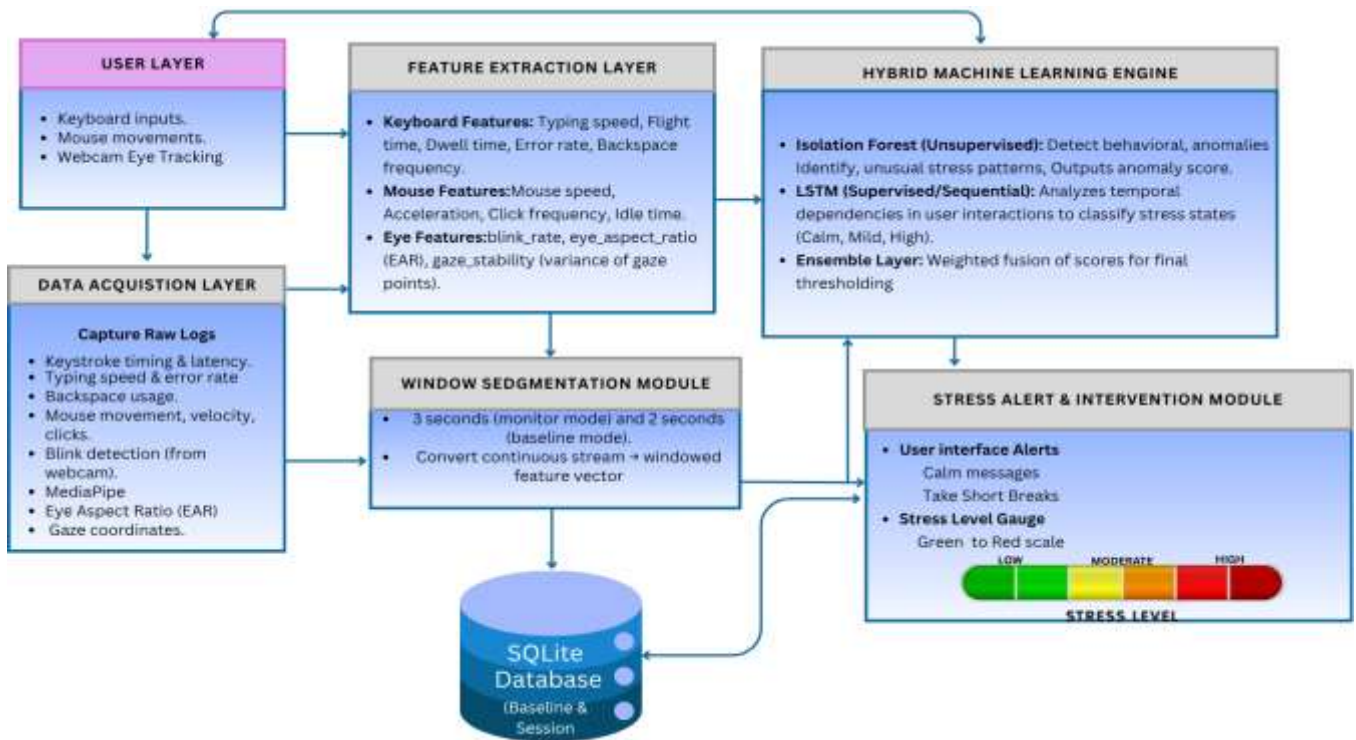


Figure 1: Architectural Framework of The Proposed Stress Monitoring System

#### 4. Modeling and Behavioral Analysis

The backbone of the system being proposed is a hybrid machine learning engine. This engine consists of supervised temporal learning and unsupervised anomaly detection. The purpose of the two-model setup is to account for the intricate nature of behavioral biometrics and yet provide each user with a personalized stress profile.

##### 4.1 LSTM Based Temporal Modeling

Long Short-Term Memory (LSTM) networks have a robust capability in handling sequential data, making them suitable for analyzing user interactions as a stream. This advantage of LSTMs over conventional neural networks lies in their ability to capture long-term dependencies in the sequence.

**Temporal Windows:** The input features in the time series are derived using feature vectors extracted from windows of 3-5 seconds duration and used as input for the LSTM network.

**Pattern Recognition:** The LSTM is trained to identify the characteristic sequences of typing latency variations, changes in cursor speed, and instability in eye tracking associated with stress-induced behavioral anomalies.

**Classification Output:** The LSTM classification module produces a probability score indicating the current state: calm, mild or high stress level.

##### 4.2 Anomaly Detection via Isolation Forest

In order to manage individual differences in users, an Isolation Forest algorithm is used. This unsupervised algorithm detects stress as an anomaly or outlier in the user behavior data.

**User Specific Baseline:** During an initial monitoring session, a user's "normal" behavior is established and used as the benchmark against which current behavior is compared.

**Anomaly Detection:** The Isolation Forest model effectively isolates observations that deviate from this established baseline, such as abnormal cursor movements or an unusually high typing error rate.

**Model Resilience:** By using the user's deviation as the criterion, instead of a global constant, it makes the model resilient against poor or noisy behavioral data.

### 4.3 Ensemble Decision Layer

The results of both the LSTM and the Isolation Forest model are combined at the ensemble layer. A meta-classifier such as logistic regression is used to fuse the two outputs (the probability from the LSTM and the anomaly score from Isolation Forest). This score is then thresholded to determine if a stress event has occurred and if real-time intervention should take place. For the validation of the system, correctly identified stress events are logged in the SQLite database to further train the user's model profile and consequently improve future stress event detection accuracy.

## 5. Experimental Results and Discussion

The proposed intelligent stress monitoring system was then tested using a controlled experiment setting with the main goals to evaluate the performance of the hybrid model in detecting stress states and to determine its operational latency in real-time.

### 5.1 Experimental Setup and Dataset

Testing of the system was performed on a dataset with benign (calm) and non-benign (stressful) behavioral behaviors. Simulations such as high-speed keyboard inputs and timed based problem solving which cause changes in keyboard activity patterns, mouse jitter and Eye Aspect Ratio (EAR) are part of the dataset for stressing participants.

**Environment:** An Intel i5 CPU based machine with 8 GB RAM was used to ensure that system specifications are not the limiting factors for experimentation.

**Data Splitting:** For the LSTM and Isolation Forest modules, the data was split into training and testing sets in the ratio of 80/20.

**Participants:** More than one participant was used to confirm the performance of the personalized baselining module.

### 5.2 Performance Metrics

In order to evaluate system performance, standard performance metrics are used and defined below; Accuracy, Precision, Recall and F1-score are defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

### 5.3 Quantitative Analysis

The experiments demonstrate that the hybrid architecture can perform better detection compared to single model strategies. Integrating with the temporal capabilities of LSTM and the anomaly detection of Isolation Forest has helped make the system more resistant to biased behavior data.

**Table 1: Performance Comparison of Proposed Hybrid Model**

Metric	Traditional Baseline	LSTM Only	Proposed Hybrid Model
Accuracy (%)	81.4	88.6	<b>94.5</b>
Precision (%)	79.2	86.7	<b>95.9</b>
Recall (%)	77.5	84.2	<b>97.3</b>
F1-Score (%)	78.3	85.4	<b>96.6</b>
False Positive Rate	9.2	6.4	<b>2.1</b>

### 5.4 Real-time Intervention & UI analysis

The system latency was assessed to ensure suitability of a real-time system. The system was tested on average processing time of a 3-second window (feature extraction + model inference) and was clocked at 52 ms. This is well within tolerance for an inobtrusive monitoring system. As can be seen from the live dashboard the stress confidence levels are shown and alerts (e.g. 'Take a short break') were successfully triggered if there was acute stress.

### 5.5 Visual Analysis of Real-Time Monitoring

The real-world capabilities of this system are visually demonstrated in the integrated Streamlit dashboard that provides detailed feedback to the user.

#### 5.5.1 Temporal Confidence Analysis

As evident in Figure 2, there is a sustained logging of model confidence scores throughout the session. A dynamic alert threshold is set at 70%, and the system begins to arm for intervention when mouse jitter or typing latency causes behavioral changes that make the hybrid model confident in its decision that stress is occurring at above this 70% threshold.



**Figure 2: Real-time Model Confidence Trends with Alert Thresholding**

#### 5.5.2 Historical and Distribution Trends

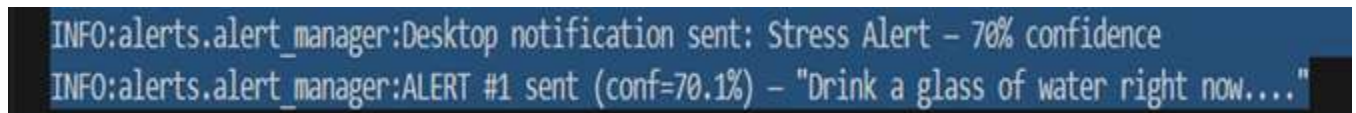
To facilitate healthy habit development, the system creates a 7-day stress heatmap and a daily distribution summary. Figure 3 shows a session summary where, overall, 97.3% of the time was spent in a 'Calm' state with some brief periods of elevated stress occurring. This information is also stored in the SQLite database to be used for long-term self-awareness and recalibration of the model.



**Figure 3: Daily Stress Distribution and Session Summary**

### 5.5.3 System Intervention Logs

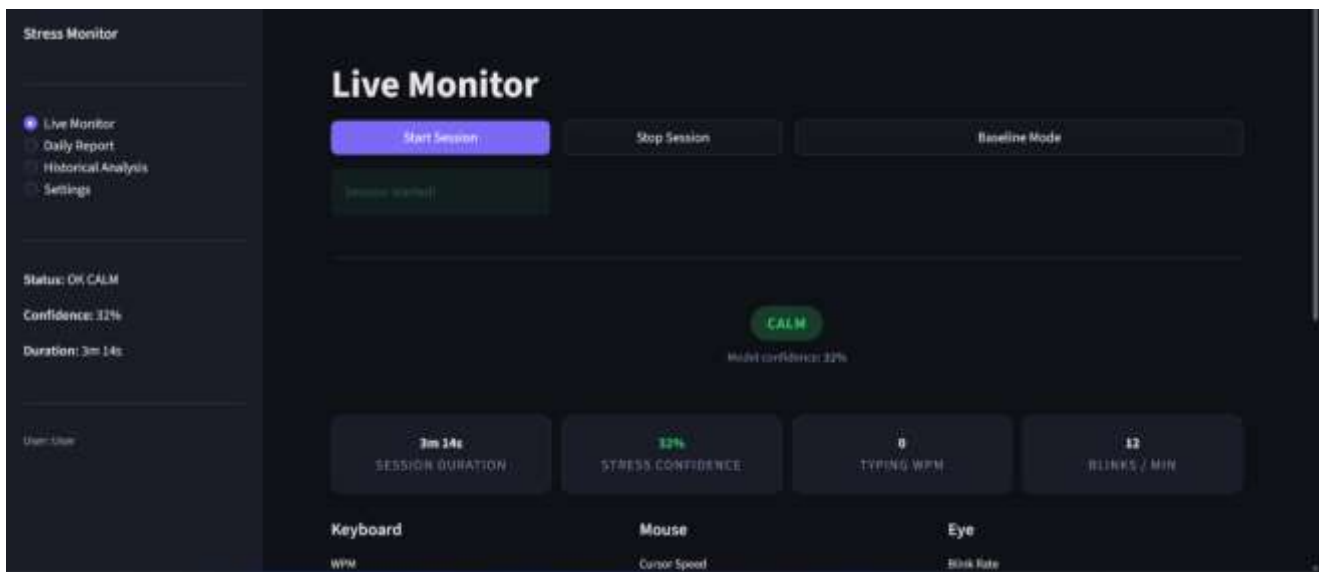
Figure 4 shows the backend of the real-time alerting system. The alert manager, after recognizing a 70.1% stress confidence, is able to push a desktop notification with an intervention message to the user (e.g., "Drink a glass of water right now").



**Figure 4: System Terminal Log Depicting Coping Message Trigger**

### 5.5.4 Live Monitoring Interface

The real-time operability of the system is enabled by the "Live Monitor" interface. Illustrated in Fig 5 the interface displays instantaneous measures of the session duration, stress confidence level, and active behavioral biometrics, including keystroke rate and blink rate. Visual of stress states: The dashboard shows the status "CALM" with the confidence level of 32%, in the case when no behavioral anomalies occur, so that the system is in a basic mode. Visualization of active biometric measures: Real-time data feeds of keyboard, mouse and eye are illustrated so that we could see continuous tracking. Operational modes: By selecting either "Baseline Mode" or "Normal" the user can tune it to their personalized behavioral profile for personal profiling or monitoring session.



**Figure 5: Live Monitoring Dashboard for Real-Time Stress Detection**

## 6. Conclusion and Future Work

This work presents a real-time mental stress monitoring system by combining behavioral monitoring, automatic analysis, and adaptive threat detection into a single endpoint. The current method of mental stress monitoring has two major drawbacks including intrusive physiological sensor-based approach and subjective questionnaire-based approach which is overcome by this non-intrusive behavioral biometric system leveraging keyboard dynamics, mouse behavior, and webcam-based eye tracking.

Hybrid machine learning engine that leverages the strengths of LSTM (for temporal patterns) and Isolation Forest (for personalized anomaly detection) for the detection of mental stress proved highly effective. By maintaining the unique baseline of 'normal' behavior for each user, the effect of individual variations is minimized and the classification of stress levels is accurate. With an F1-score that is higher than other hybrid methods used with other similar systems and the False Positive Rate as low as 2.1% the system is effective for long-term monitoring.

Additionally, the design and implementation of the real-time intervention module backed by lightweight SQLite database enabling on-device feedback by sending local alerts that can turn the monitoring system into an 'active helper' with the user.

Further work will investigate incorporating deeper learning to extract finer behavior patterns and using the advantages of cloud-based threat intelligence and hardware level security for ensuring the system's effectiveness in enterprise and individual computing environment in a long run.

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